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Team performance according to ball possession characteristics: A social networks approach

Dissertação elaborada com vista à obtenção do Grau de Mestre em Treino de Alto Rendimento

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“O rio atinge os seus objectivos porque aprendeu
a contornar os obstáculos.” **Lao Tsé**

“O importante não é justificar o erro, mas sim
impedir que ele se repita.” **Che Guevara**

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Resumo

Ao longo dos últimos anos, o futebol entrou num período de acesso rápido a uma grande quantidade de dados de análise de jogo. As redes sociais têm sido adoptadas para revelar a estrutura e organização da rede de interacções, como as tendências de passe dos jogadores. Neste estudo investigou-se a influência das características posse de bola no sucesso competitivo das equipas Espanholas de *La Liga*.

A amostra foi composta por dados brutos da distribuição de passe da OPTA (n = 269.055 passes) obtidos a partir de 380 jogos onde estão envolvidas todas as 20 equipas da temporada 2012/2013. Então, geramos 760 matrizes de adjacência e as suas redes sociais correspondentes, utilizando o software Node XL. Para cada rede foram calculadas três medidas de desempenho da equipa de forma a avaliar as tendências da posse de bola: graph density, average clustering e passing intensity. Foram identificados três níveis de sucesso competitivo utilizando uma análise de grupos a dois níveis com base em duas variáveis: O total de pontos marcados por cada equipa e o rácio de golos marcados por golos sofridos.

A nossa análise revelou diferenças significativas entre desempenhos competitivos em todas as três medidas de desempenho da equipa (p <0,001). As equipas classificadas no fundo do ranking apresentaram menor número de jogadores conectados (graph density) e triangulações (average clustering) do que as equipas com ranking intermédio e de topo. No entanto, todos os três grupos divergiram em termos de intensidade de passe (passing intensity), sendo que as equipas de topo do ranking têm um maior número de passes por tempo de posse de bola, do que as equipas com ranking intermédio ou baixo. Finalmente, foram encontradas semelhanças e diferenças nos padrões de jogo das 20 equipas utilizando Cohen's effect size.

Em suma, os resultados sugerem que o desempenho competitivo foi influenciado pela densidade e conectividade das equipas (Graph density and average clustering, respectivamente), principalmente devido à forma como as equipas usam o seu tempo de posse de bola para dar intensidade ao seu jogo.

Abstract

Over the last few years, football entered in a period of accelerated access to large amount of match analysis data. Social networks have been adopted to reveal the structure and organization of the web of interactions, such as the players passing distribution tendencies. In this study we investigated the influence of ball possession characteristics in the competitive success of Spanish *La Liga* teams.

The sample was composed by OPTA passing distribution raw data (n=269,055 passes) obtained from 380 matches involving all the 20 teams of the 2012/2013 season. Then, we generated 760 adjacency matrixes and their corresponding social networks using Node XL software. For each network we calculated three team performance measures to evaluate ball possession tendencies: graph density, average clustering and passing intensity. Three levels of competitive success were determined using two-step cluster analysis based on two input variables: the total points scored by each team and the scored per conceded goals ratio.

Our analyses revealed significant differences between competitive performances on all the three team performance measures ($p < .001$). Bottom-ranked teams had less number of connected players (graph density) and triangulations (average clustering) than intermediate and top-ranked teams. However, all the three clusters diverged in terms of passing intensity, with top-ranked teams having higher number of passes per possession time, than intermediate and bottom-ranked teams. Finally, similarities and dissimilarities in team signatures of play between the 20 teams were displayed using Cohen's effect size.

In sum, findings suggest the competitive performance was influenced by the density and connectivity of the teams, mainly due to the way teams use their possession time to give intensity to their game.

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Introduction

1. Introduction

Football is a complex phenomenon mainly due to the intricate interpersonal interactions developed by team players across time. These interactions have been somewhat neglected by researchers when investigating passing trends underlying the possession game (or ball possession). In an interactive and functional way, analysing passing trends would imply capturing how pairs of players link themselves by passing the ball between each other (Passos et al., 2010). These tendencies shape preferential passing interaction tendencies within particular sub-units of a team, which consequently scale and shape the global (team) patterns of on-field ball displacements (Duch, Waitzman and Amaral, 2010). This emergent process arises once the team players share the same general intentions and goals, and are linked by common informational means (Duarte & Frias, 2011). This creates interdependence between team players and also between the individual and team behaviours (Bar-Yam, 2004).

Conceptualizing and analysing passing trends based on these interactive behaviours may allow shedding some light on the current debate on the relevance of ball possession performance indicators. There are two different points of view. From one hand, some studies did not found any relation between ball possession indicators and performance outcomes (e.g., Bate, 1998; Stanhope, 2001). On the other hand, other authors found significant and positive associations between competitive success and ball possession (e.g. Hook and Hughes 2001; Jones et al., 2004; Lago-Peñas & Dellal, 2010). Based on these controversial findings, Collet (2013) performed a systematic investigation on this topic, examining a range of ball possession indicators in several competitive contexts, from European and World Cup tournaments to high-standard European football leagues. His findings revealed poor reliability of several ball possession indicators, showing that much of the success behind the 'possession game' is thus a function of elite teams confined in geographic and competitive space (e.g., Barcelona in Spain, Manchester United in England). Therefore, it seems researchers need to find alternative methods to inspect specific ball possession characteristics that better account for variant strategic environments (James et al., 2002) and specific teams' signatures of play (Paixão, Sampaio, Almeida & Duarte, 2015), seeking to associate it with the performance outcomes (Araya & Larkin, 2006).

One way to capture the specific interactive passing trends characterizing a team's ball possession is the use of social networks analysis. For instance, Grund (2012) found that successful Premier League teams are characterized by higher passing work-rate and low centralization, compared to less successful teams. This means successful teams use the ball more intensively, exchanging it more frequently among a higher number of team players and, consequently, depending less on a single or few centralized/influential players. These findings agreed with suggestions from longitudinal studies showing an increase of both the number of passes and the pass completion rate as soccer evolutionary game trends (Wallace & Norton, 2014; Barnes, Archer, Hogg, Bush & Bradley, 2014). Using also social networks analysis, Duch, Waitzman and Amaral (2010) found a positive association between low centralization (highly distributed work) and the performance outcome of the 2008 European Cup winner (Spain). Another interesting feature of successful teams may be also the players' capacity to cluster together when passing the ball. This style of play was consistently observed in the 2010 FIFA World Cup winner, the Spanish squad, mainly across the three final knock-out matches, in which the clustering coefficient values of the pass network remained high (Lopez & Touchette, 2012; Cotta, Mora, Merelo & Merelo-Molina, 2013). This data is consistent with other findings from Yamamoto & Yokoyama (2011), which showed a positive relationship between the number of triangles (i.e., three connected nodes in a passing sequence) and the successful attacks and shots produced by teams. This style of play has been anecdotally linked to the famous Barcelona's '*tiki-taka*'. In this vein, Gyarmati and Kwak (2014) revealed this famous style of play does not consist of uncountable random passes but rather has a precise and finely singular structure. Contrary to all the teams from the five top-ranked soccer leagues, Barcelona revealed higher frequencies of pass motifs implying ball exchanges between: (i) pairs of players in a to-and-fro fashion, and; (ii) open triplets (i.e., three players connected by a minimum of two passes).

Despite all this recent insights on the relation of passing networks characteristics and performance outcome, research on soccer match analysis using social networks is still in its infancy. And as Mackenzie and Cushion (2014) pointed, an important factor that should be taken into account is the social-cultural constraints in which case studies, or studies with low sample sizes, are performed. For instance, to what we know successful English teams are characterized by higher passing work-rate and low centralization. But, to what extent may the results found in Premier League transfer to other competitive contexts?

The purpose of this study was to examine the association of passing networks characteristics with the competitive success of Spanish *La Liga* teams. Moreover, we intend to analyse similarities in teams' signatures of play between the 20 competing teams, using team level metrics. Based on the studies of Grund (2012) and Lopez and Touchette (2012), we hypothesized top-ranked teams must display higher passing work-rates, higher levels of clustering and more distributed passing flows, compared to bottom-ranked teams.

2. Method:

2.1 - Sample

The study is based on a sample of all the successful passes (n=269,055) performed during the entire Spanish *La Liga* 2012/2013 season, gathered from the total of 380 matches. Table 1 displays sample characteristics, with an emphasis in the passing actions and percentage of effective possession time.

Table 1 – Total number of passes and effective ball possession time across all teams in the Spanish *La Liga* 2012/2013 season.

Ranking	Team	Total Number of Passes	% effective ball possession time ($\bar{x}$ ± SD)
1	Barcelona	26613	38.855 ± 5.200
2	Real Madrid	15960	27.434 ± 6.031
3	At. Madrid	12816	23.870 ± 4.740
4	Real Sociedad	14158	25.912 ± 5.393
5	Valencia	13928	25.625 ± 4.947
6	Málaga	14974	25.724 ± 4.318
7	Real Betis	12234	22.467 ± 4.312
8	Rayo Vallecano	14167	25.006 ± 4.307
9	Sevilla	14470	26.357 ± 6.105
10	Getafe	11243	21.603 ± 4.505
11	Levante	8843	18.311 ± 3.333
12	At. Bilbau	15157	26.681 ± 5.189
13	Espanyol	10866	21.107 ± 5.237
14	Valladolid	14240	25.221 ± 5.388
15	Granada	10325	21.379 ± 4.214
16	Osasuna	11257	22.839 ± 4.539
17	Celta Vigo	13297	23.911 ± 4.046
18	Mallorca	10208	20.938 ± 5.316
19	Deportivo	13542	24.591 ± 4.840
20	Zaragoza	10757	21.819 ± 4.767

Passing distribution raw data were obtained through the OPTA notation system. Reliability of this system was demonstrated in literature by Liu *et al.*, (2013).

2.2 - Procedures and Variables

To determine the teams' competitive success, we used the total number of points and the ratio of scored per conceded goals. A two-step cluster analysis was used to determine the competitive success/outcome clusters based on these indicators.

2.2.1- competitive success through cluster analysis

The two-step cluster analysis divided the teams in 3 clusters of competitive success with an average silhouette of 0.70 (Predictor importance: goals ratio = 1.00, points earned = 0.83). Table 2 displays the results and the cluster number of each team.

Table 2 – Performance indicators according to competitive success

Ranking	Team	Points	GS*	GT**	Goals Ratio	Cluster
1	Barcelona	100	115	40	2.875	1
2	Real Madrid	85	103	42	2.452	1
3	Atlético Madrid	76	65	31	2.097	1
4	Real Sociedad	66	70	49	1.429	2
5	Valência	65	67	54	1.241	2
6	Málaga	57	53	50	1.060	2
7	Real Bétis	56	57	56	1.018	2
8	Rayo Vallecano	53	50	66	0.758	2
9	Sevilla	50	58	54	1.074	2
10	Getafe	47	43	57	0.754	3
11	Levante	46	40	57	0.702	3
12	Athletic	45	44	65	0.677	3
13	Espanyol	44	43	52	0.827	3
14	Valladolid	43	49	58	0.845	3
15	Granada	42	37	54	0.685	3
16	Osasuna	39	33	50	0.660	3
17	Celta de Vigo	37	37	52	0.712	3
18	Mallorca	36	43	72	0.597	3
19	Deportivo	35	47	70	0.671	3
20	Zaragoza	34	37	62	0.597	3

*GS – Goals Scored; **GT – Goals Taken

Two-step cluster analysis divided final classification in three clusters and each cluster is composed by a different number of teams. Differences between clusters are evident through greater similarities among teams when compared to the other clusters members. Thus, cluster 1 (Top-ranked teams) is composed by the first three teams in the league table. The cluster 2 (intermediate-ranked teams) is composed by the next six teams. The third cluster (Bottom-ranked teams) is composed by the last 11 teams in the league final ranking.

2.2.2 – Ball possession Characteristics

The ball possession characteristics were measured through the following team passing network measures:

(i) Graph Density is an overall measure of the inter-connectedness of vertices and it was obtained by the ratio between the number of total edges in a graph and the maximum number of possible edges within a graph (Freeman, 1979):

$$D = \frac{N.^{\text{o}}\ e}{N.^{\text{o}} \max\ e}$$

Maximal density is 1 and minimum density is 0 (Coleman & Moré, 1983). Frequent ball exchange among a higher number of team players tends to approach to 1. Consequently, higher team density supports denser passing work rates (more total edges).

(ii) Team Clustering was obtained as the sum of local clustering coefficients of all the team players. The individual clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together (Holland & Leinhardt, 1971; Watts & Strogatz, 1998). This is the measure of how connected node's neighbours are to one another. In a functional way it is the number of edges connecting node's neighbours divided by total number of possible edges between the node's neighbours:

$$Ci = \frac{\text{Number of triangles connected to node } i}{\text{Number of triples centered around node } i}$$

Functionally, Team Clustering captures players' capacity to cluster together when passing the ball in a sequence of two or more passes by pairs of players. It is obtained as follows:

$$Ct = \Sigma Ci$$

(iii) Pass Intensity was given by the total number of successful passes by the percentage of ball possession. This is an arbitrary unit measure of how ball possession is exchanged and used by a team.

$$I = \frac{\Sigma Passes}{\%Ball\ possession}$$

This intensity measure was adapted from Grund (2012) work. The higher values are equivalent to high frequency of passing per time unit. These team measures were obtained from the passing networks of each team during the entire matches. Social networks analysis was performed using Node XL software.

To inspect teams' signatures of play we developed adjacency matrixes of the 20 analysed teams, based on the Cohen's *d* effect size values (Cohen, 1988) between each pair of teams.

$$d = \frac{\bar{x}1 - \bar{x}2}{s}$$

Then, a dissimilarity network (Borgatti, Mehra, Brass & Labianca, 2009) was created for each team measure (i.e., graph density, team clustering and pass intensity), in which the nodes were the teams and the edges were the Cohen's *d* values. These dissimilarity networks allow identifying pairs of teams with high degree of similarity and with larger differences for each of the passing network characteristic.

2.3 - Inferential Statistics

One-way ANOVAs, with Games-Howell's post hoc tests, were used to examine differences in ball possession characteristics (graph density, team clustering and pass intensity) according to the competitive success.

All the statistical analyses were done in IBM SPSS Statistics 20, maintaining a significance level of 5%.

Results

3. Results

3.1 - Competitive success and passing networks

Table 3 shows the influence of the competitive success according to the passing networks characteristics.

Table 3 – Passing networks characteristics according to the competitive success.

Competitive Success	Graph Density		Team Clustering		Pass Intensity	
	$\bar{x}$ ± SD	Sig.	$\bar{x}$ ± SD	Sig.	$\bar{x}$ ± SD	Sig.
Top-ranked teams cluster 1 (n=3)	.745 ± .058		11.546 ± .657		15.737 ± 2.092	
Intermediate-ranked teams cluster 2 (n=6)	.733 ± .061	.001	11.456 ± .567	.001	14.651 ± 1.393	.001
Bottom-ranked teams cluster 3 (n=11)	.704 ± .072		11.032 ± .731		13.382 ± 1.569	
	C1=C2>C3**		*C1=C2*>C3**		*C1**>C2**>C3***	

Games-Howell's post hoc test, * $p < .001$; ** $p \leq .002$

Two-way ANOVAs showed significant interaction effect between Success*Teams in all three measures, $F(2,379)=7.105, p<.001$, $\eta^2=.273$

This means that although the global trend to observe significant effects according to the final ranking, teams tend to display different passing networks characteristics within each cluster. Thus, we decided to inspect all the teams based on the notion of signatures of play using similarities networks.

3.2 – Team Similarities

Descriptive statistics of the variables for each team used in the analysis are presented in table 4

Table 4 –Team variables descriptive values.

Ranking	Team	Graph Density $\bar{X} \pm SD$	Team Clustering $\bar{X} \pm SD$	Pass Intensity $\bar{X} \pm SD$
1	BAR	.770 ± .043	11.800 ± .337	17.750 ± 1.252
2	RM	.755 ± .053	11.803 ± .621	15.317 ± 1.754
3	ATM	.707 ± .060	11.034 ± .655	14.144 ± 1.352
4	RSOC	.730 ± .087	11.307 ± .621	14.232 ± 1.487
5	VAL	.725 ± .043	11.396 ± .520	14.004 ± .959
6	MAL	.739 ± .051	11.656 ± .493	15.455 ± .700
7	RBET	.727 ± .072	11.217 ± .591	14.019 ± 1.526
8	RVALL	.732 ± .054	11.512 ± .567	15.723 ± 1.132
9	SEV	.745 ± .051	11.652 ± .525	14.472 ± 1.407
10	GET	.691 ± .055	11.134 ± .506	13.315 ± 1.063
11	LEV	.668 ± .070	10.765 ± .746	12.399 ± 1.180
12	ATBIL	.761 ± .077	11.485 ± .676	15.432 ± 1.160
13	ESP	.678 ± .091	10.704 ± .585	12.935 ± 1.150
14	VALL	.717 ± .063	11.153 ± .736	14.285 ± 1.383
15	GRA	.670 ± .067	10.385 ± .738	12.261 ± 1.070
16	OSA	.707 ± .063	11.284 ± .964	12.737 ± .907
17	CVIG	.716 ± .062	11.213 ± .541	13.730 ± 1.223
18	MALL	.701 ± .059	10.892 ± .637	13.237 ± 1.553
19	DEP	.730 ± .084	11.293 ± .708	14.771 ± 1.529
20	ZAR	.700 ± .057	11.054 ± .532	12.106 ± .967

Table 5 presents significant values for multiple comparisons concerning graph density measurements.

Table 5 - Graph Density multiple comparisons

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
BAR	-									*	*		*		*					
RM		-									*		*		*					
ATM			-																	
RSOC				-																
VAL					-															
MAL						-														
RBET							-													
RVALL								-												
SEV									-		*									
GET	*									-										
LEV	*	*							*		-	*								
ATBIL											*	-	*		*					
ESP	*	*										*	-							
VALL	*	*										*		-						
GRA															-					
OSA																-				
CVIG																	-			
MALL																		-		
DEP																			-	
ZAR																				-

The mean difference is significant at the $p < .05$

There was a main effect of Team, $F(19,379)= 2.734$, $p<.001$, $\eta^2 =.114$

Figure 1 shows the teams' dissimilarity network of graph density, based on Cohen's *d* effect size values (Table in supplementary materials).

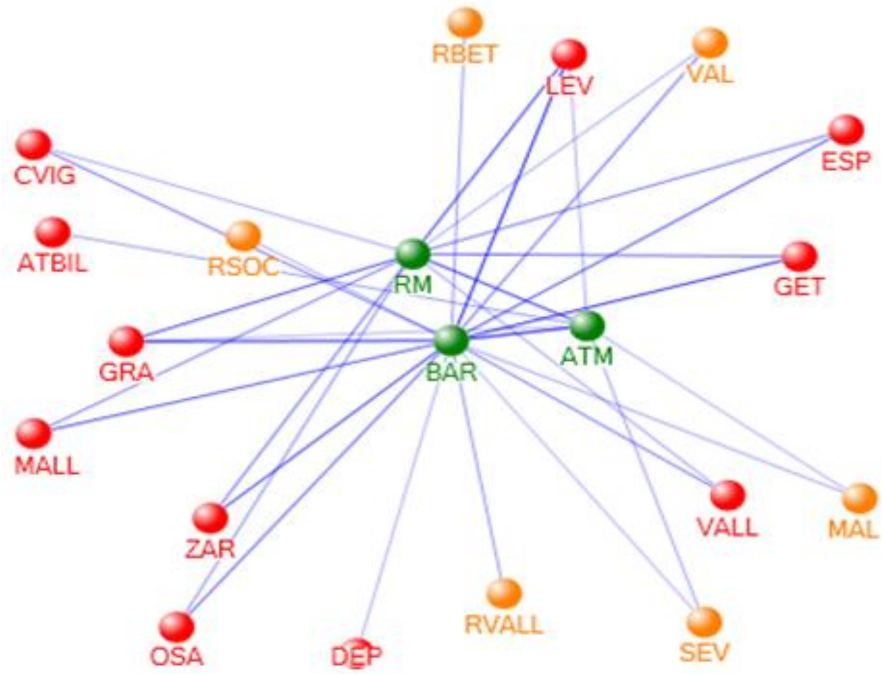

Figure 1 – Graph Density dissimilarity network

Table 6 represents significant values for multiple comparisons concerning the Team Clustering

Table 6 – Team Clustering multiple comparisons.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
BAR	-		*								*		*		*			*		
RM		-	*								*		*		*			*		
ATM	*	*	-																	
RSOC				-											*					
VAL					-										*					
MAL						-					*		*		*			*		
RBET							-								*					
RVALL								-					*		*					
SEV									-		*		*		*			*		
GET										-										
LEV	*	*				*			*		-									
ATBIL												-	*		*					
ESP	*	*				*		*	*			*	-							
VALL														-	*					
GRA	*	*		*	*	*	*	*	*			*		*	-	*	*		*	
OSA															*	-				
CVIG															*		-			
MALL	*	*				*			*									-		
DEP															*				-	
ZAR																				-

The mean difference is significant at the $p < .05$

There was a main effect of Team, $F(19,379)= 4.448$, $p< .001$, $\eta^2 = .174$

Figure 2 shows the teams' dissimilarity network of team clustering, based on Cohen's *d* effect size values (Table in supplementary materials).

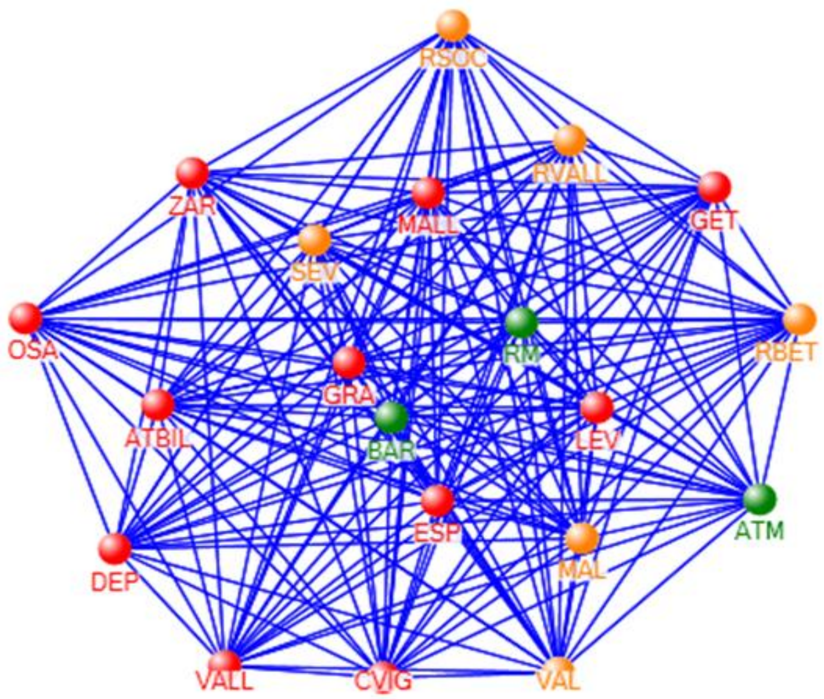

Figure 2 - Team Clustering dissimilarity network

Table 7 presents significant values for multiple comparisons concerning to Pass Intensity.

Table 7 – Pass Intensity multiple comparisons.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
BAR	-	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
RM	*	-								*	*		*		*	*	*	*		*
ATM	*		-					*			*				*					*
RSOC	*			-				*			*				*					*
VAL	*				-			*			*				*					*
MAL	*					-				*	*		*		*	*	*	*		*
RBET	*						-	*			*				*					*
RVALL	*		*		*		*	-		*	*		*		*	*	*	*		*
SEV	*								-		*		*		*					*
GET	*	*				*		*		-		*								
LEV	*	*	*	*	*	*	*	*	*		-	*		*					*	
ATBIL	*									*	*	-			*	*	*	*		*
ESP	*	*				*		*	*			*	-						*	
VALL	*										*			-	*	*				*
GRA	*	*	*	*	*	*	*	*	*			*		*	-				*	
OSA	*	*				*		*	*			*		*		-			*	
CVIG	*	*				*		*				*					-			*
MALL	*	*				*		*				*						-	*	
DEP	*										*		*		*	*		*	-	*
ZAR	*	*	*	*	*	*	*	*	*			*		*			*		*	-

The mean difference is significant at the $p < .05$

There was a main effect of Team, $F\,(19,379) = 14.802$, $p < .001$, $\eta^2 = .411$

Figure 3 shows the teams' dissimilarity network of pass intensity, based on Cohen's *d* effect size values (Table in supplementary materials).

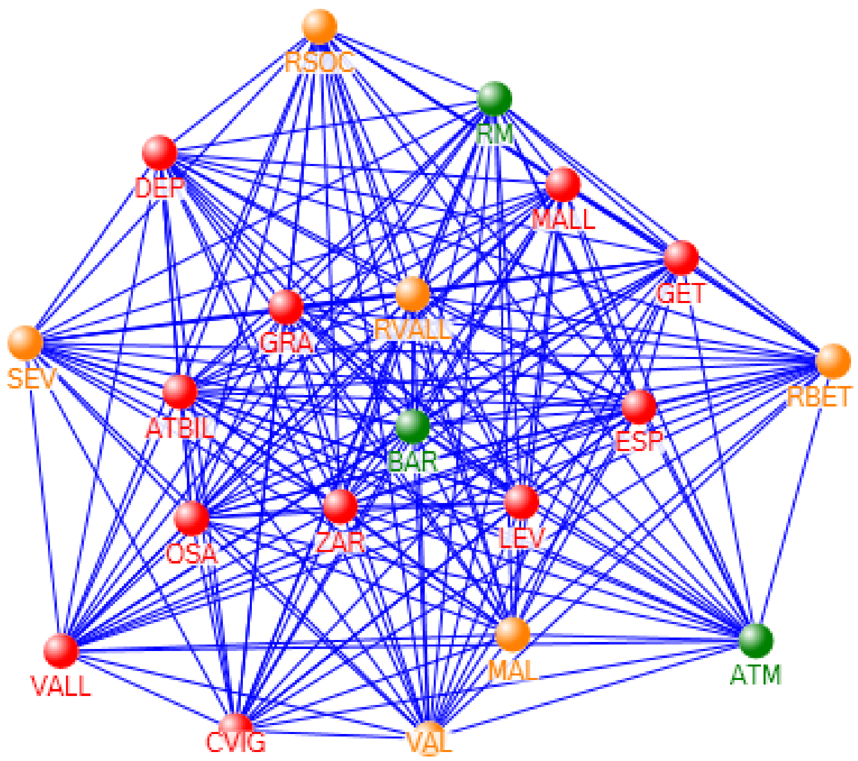

Figure 3 - Pass Intensity dissimilarity network

4. Discussion

The aim of this study was to examine the association between passing networks characteristics and the competitive performance of Spanish *La Liga* teams. Although the relation between ball possession and outcome is yet controversial, some literature suggests that different signatures of play may exist in successful and unsuccessful teams (e.g., Lago-Peñas *et al*., 2011). Although the specificity of each team's signature of play, the data obtained in this study generally supports the notion that teams tend to display passing networks with different properties as a function of the final position in the league ranking, i.e., the competitive success.

The graph density results indicated that top and intermediate-ranked teams showed higher number of players connected by passing edges than bottom-ranked teams. Also, top- and intermediate-ranked teams displayed a higher tendency for the players cluster together, compared to bottom-ranked team players. These findings are in line with prior studies. For instance, the denser passing networks were associated to the more successful Premier League teams (Grund, 2012). Also, Lopez and Touchette (2012) found the two finalist teams of the 2010 FIFA World Cup (Spain and Netherlands) were the teams with higher connectivity (i.e., density) from the last 16 stage. The team clustering of Spain and Netherlands' passing networks were also the highest, while keeping lower betweenness scores. According to the same authors, this is a reflection of the 'total football' and '*tiki-taka*' styles, in which well-connected players constantly pass the ball around. This last style of play was linked somewhere with higher frequency of triplets (Gyarmati & Kwak, 2014), such as we observed in the top-ranked teams of the present study. The two best-classified teams of our sample (Barcelona and Real Madrid) were clearly the two teams with higher team clustering values. These findings in soccer agreed with studies of team performance in other natural contexts, in which densely configured interpersonal ties were associated to higher levels of goal achievement and a commitment to stay together (i.e., team viability) (Balkundi & Harrison, 2006).

Concerning pass intensity, our analyses revealed significant differences between the three clusters of competitive success. Top-ranked teams showed the greatest values, followed by the intermediate and bottom-ranked teams, respectively. Thus, teams that use its possession time to give pass intensity to its game tended to finish the competition as a top-ranked team. On the contrary, teams with low passing work-rate tended to rely on unwanted bottom positions in the final league ranking. This data is in agreement with findings of Grund

(2012) in Premier League teams, suggesting a potential generalisation of this notion for competitive contexts others than England and Spain professional leagues. This finding also underlines the importance the passing actions have in contemporary soccer, either quantitatively with a trend for an increase in the number of passes per game (Wallace & Norton, 2014), but also qualitatively, with the increase in the percentage of passing accuracy (Barnes et al., 2014). Since the game time in play tend to decrease (Wallace & Norton, 2014), although the mentioned increase in the number and quality of passing actions, the pass intensity seems to constitute a key performance indicator discriminating successful team performance in soccer (Hughes & Bartlett, 2002; Rampinini, 2009)

Despite the differences found in passing networks characteristics according the final position in *La Liga* ranking, an inspection of mean values suggested some teams within a common cluster are more similar than others. Thus, we examined teams' similarities starting from the idea that each team has its own signature of play (Hughes & Reed, 2005). For example, Paixão et al. (2015) demonstrated that top-ranked European teams tended to differently adapt the length of their passing sequences as a function of the evolving scoreline. Here, we tried to determine the existence of similarities through Cohen's *d* effect size measures and qualitatively analyse the topological distribution of teams.

Regarding to the higher graph density teams, Barcelona, Real Madrid and Sevilla (.770±043; .755±.053; and .745±.051, respectively), are all top and intermediate-ranked teams. For the lower values there are teams like Levante, Granada and Espanyol (.668±.070; .670±.067 and .678±.091, respectively, see Table 4), all of those belong to bottom-ranked teams. On team clustering, teams with higher values were Real Madrid, Barcelona, Málaga and Sevilla (11.203±.629; 11.800±.337; 11.656±.493 and 11.652±.525, respectively), which relied on top and intermediate-ranked teams. On the contrary, the lower team clustering values were obtained by teams with less triangular passing combinations, such as Granada, Espanyol, Levante and Mallorca (10.385±.738; 10.704±.585; 10.765±.746 and 10.892±.637, respectively), which relied on the bottom cluster. This is an indicator of similarities and we suggest it is possible to identify higher values of graph density and team clustering as a signature of play of successful Spanish *La Liga* teams. This can also be seen on graph 1 and 2 where it is also possible to check the few connection of some nodes.

The other measure in study, pass intensity, revealed some interesting details on teams' similarities networks. The league winner, Barcelona, revealed the highest pass intensity value (17.750±1.252). This measure clearly places Barcelona away from Zaragoza (12.106±.967) or Granada (12.261±1.070), teams relying on the bottom half of the league ranking. There are other intermediate teams in league ranking which displayed also intermediate pass intensity values, such as Sevilla, Valencia or even At. Bilbau (14.472±1.407; 14.004±.959 and 15.432±1.160, respectively). Through networks pass intensity topological representation (see Figure 3), it is possible to confirm Barcelona's low similarity with others bottom-ranked teams (red nodes), which are tightly connected apart between themselves. A strong connection between them (Blue loaded dash), e.g. Zaragoza, Granada, Levante, Mallorca, Osasuna and Espanyol, reveals that a typical signature of play of bottom-ranked teams may be slow passing flows. It is also possible to observe weaker ties (light blue dash) between top-ranked (green nodes) and intermediate-ranked teams (orange nodes), e.g. Real Madrid, Sevilla and Real Sociedad, to bottom-ranked teams (red nodes). Importantly, it is also possible to observe a strong tie between Barcelona and Real Madrid, the first and second teams in the final league ranking.

5. Conclusion

Our work confirms previous findings about the link between levels of interaction and density with competitive success through passing networks. Higher levels of open triplets and low centrality lead to greater competitive success. These results are greater has teams' pass intensity increase (Grund, 2012, Lopez & Touchette, 2012).

Despite the differences in passing network characteristics, some teams within a common cluster tend to resemble. Our findings suggest there are similarities when using higher values of graph density and team clustering. When using pass intensity as an indicator it is easier to identify different signatures of play due to the existing dissimilarities between all clusters.

References

6. References

1. Araya, J. A. & Larkin, P. (2006). Key performance variables between the top 10 and bottom 10 teams in the English Premier League 2012/13 season. University of Sidney papers in HMHCE, 17-23.
2. Balkundi, P. & Harrison, D. A. (2006). Ties, leaders and time in teams: Strong inference about network structure´s effects on team viability and performance. *Academy of Management Journal*, 49:1, 49-68.
3. Barnes, C., Archer, D. T., Hogg, B., Bush, M. & Bradley, P. S. (2014). The evolution of physical and technical performance parameters in the English Premier League. *International journal of Sports Medicine*, 35, 1095-1100. DOI: 10.1055/s-0034-1375695
4. Bar-Yam, Y. (2004). Making things work. Cambridge, MA: NECSI Knowledge Press.
5. Bate, R. (1988). Football chance: tactics and strategy. *Science and Football* (edited by T. Reilly, A. lees, K. Davids and W. Murphy), London: E & FN Spon, 293-301
6. Borgatti, S.P., Mehra, A., Brass, D. and Labianca, G. (2009). Network Analysis in the Social Sciences. *Science*. 323(5916),892 - 895
7. Cohen, J. (1988). Statistical power analysis for the behavior sciences. Second Edition, Department of psychology, NY University, NY, 8, 273-406
8. Coleman, T.F. & Moré, J.J. (1983). Estimation of sparse Jacobian matrices and graph coloring problems. SIAM *Journal of Numerical Analysis*, 20:1, 187-209 DOI: 10.1137/0720013
9. Collet, C. (2013). The possession game? A comparative analysis of ball retention and team success in European and International football, 2007-2010, *Journal of Sports Sciences*, 31:2, 123-136. DOI: 10.1080/02640414.2012.727455
10. Cotta, C., Mora, A. M., Merelo, J. J. & Merelo-Molina, C. (2013). A network analysis of the 2010 FIFA World Cup champion team play. *Journal of Systems Science and Complexity*, 26, 21-42. DOI: 10.1007/s11424-013-2291-2
11. Duarte, R. & Frias, T., (2011). Collective intelligence: An incursion into the tactical performance of Football teams. Faculty of Human kinetics, Lisbon, Portugal
12. Duch, J., Waitzman, J. S., Amaral, L.A.N. (2010). Quantifying the performance of individual players in a team activity. *PLos ONE* 5(6): e10937. DOI: 10.1371/journal.pone.0010937
13. Freeman, L. C. (1978). Centrality in social networks, conceptual clarification. *Social Networks*, 1, 215-239

14. Grund, T. U. (2012). Network structure and team performance: the case of English Premier League soccer teams. *Social.Networks*., DOI: 10.1016/j.socnet.2012.08.004
15. Gyarmati, L. & Kwak, H. (2014). Searching for a unique style in soccer. Qatar computing research institute. DOI: 1409.0308v1
16. Holland, P.W. & Leinhardt, S. (1971). Transitivity in structural models of small groups. Comparative Group Studies 2, 107-124
17. Hook, C. & Hughes, M. (2001). Patterns of play leading to shots in 'EURO2000'. In: *Pass.com*. Ed: CPA (Center for Performance Analysis). Cardiff: UWIC, 295-302
18. Hughes, M., & Bartlett, R. (2002). The use of performance indicators in performance analysis. *Journal of Sports Sciences*, 20:10, 739-754
19. Hughes, M. D. & Reed, D. (2005). Creating a performance profile using perturbations in soccer. Proceedings of 4th international scientific conference on kinesiology, Opatija, University of Zagreb, Croatia, September
20. James, N., Mellalieu, S. & Holley, C. (2002). Analysis of strategies in soccer as a function of European and domestic competition. *International journal of performance Analysis in sport,* 2, 85-103
21. Jones, P., James, N. & Mellalieu, S. D. (2004). Possession as a performance indicator in soccer. *International Journal of performance Analysis in Sport*, 4:1, 98-102
22. Lago-Peñas, C. & Dellal, A. (2010). Ball possession strategies in elite soccer according to the evolution of the match-score: the influence of situational variables. *Journal of Human Kinetics*, 25, 93-100
23. Lago-Peñas, C., Lago-Ballesteros, J. & Rey, E. (2011). Differences in performance indicators between winning and losing teams in the UEFA Champions League. *Journal of Human Kinetics*, 27 (III), 135-146
24. Lopez, J. & Touchette, H. (2012). A network theory analysis of football strategies. C. Clanet (ed.), *Sports Physics*: Proc. 2012 Euromech Physics of Sports Conference, 517-528. DOI:1206.6904v1
25. Liu, H. Hopkins, W., Gómez, M. Molinuevo, J. (2013). Inter-operator reliability of live football match statistics from OPTA Sports data. *International journal of performance analysis in Sport*, 13:3, 803-821
26. Mackenzie, R. & Cushion, C. (2012). Performance analysis in football: A critical review and implications for future research. *Journal of sports sciences,* 31:6, 631-676, DOI: 10.1080/02640414.2012.746720

27. Paixão, P., Sampaio, J., Almeida, C. H. & Duarte, R. (2015). How does match status affects the passing sequences of top-level European soccer teams? *International journal of Performance in Sport*, 15, 229-240
28. Passos, P., Davids, K., Araújo, D., Paz, N., Minguéns, J. & Mendes, J. (2010). Networks as a novel tool for studying team ball sports as complex social systems. *Journal of science and medicine in sport*, 14, 170-176. DOI:10.1016/j.jsams.2010.10.459
29. Rampinini, E., Impellizzeri, F.M., Castagna, C., Coutts, A.J., Wisloff, U., (2009). Technical performance during soccer matches of the Italian Serie A league: Effect to fatigue and competitive level. *Journal of Sports Science and Medicine in Sport*, 12, 227-233
30. Stanhope, J. (2001). An investigation into possession with respect to time, in the soccer world cup 1994. In: *National Analysis of Sport III*. Ed: Hughes, M.D.Cardiff, UK: UWIC. 155-162
31. Wallance, J. L. & Norton, K. I. (2013). Evolution of World Cup Soccer final games 1966-2010: Game structure, speed and play patterns. *Journal of Science and Medicine in Sport*, 17, 223-228. DOI: 10.1016/j.jsams.2013.03.016
32. Watts, D.J. & Strogatz, S.H. (1998). Collective dynamics of small-world networks. *Nature,* 393, 440-442
33. Yamamoto, Y. & Yokoyama, K. (2011). Common and unique network dynamics in football. *PLoS ONE*, 6:12: e29638. DOI:10.1371/journal.pone.002963B

Supplementary Material

Graph Density Cohen's *d* effect size matrix

	BAR	RM	ATM	RSOC	VAL	MAL	RBET	RVALL	SEV	GET	LEV	ATBIL	ESP	VALL	GRA	OSA	CVIG	MALL	DEP	ZAR
BAR	0,000	0,311	1,227	0,599	1,041	0,673	0,747	0,797	0,536	1,623	1,770	0,150	1,309	1,004	1,784	1,178	1,025	1,346	0,606	1,404
RM	0,311	0,000	0,870	0,365	0,624	0,324	0,466	0,449	0,201	1,213	1,421	0,084	1,053	0,676	1,422	0,838	0,693	0,977	0,364	1,023
ATM	1,227	0,870	0,000	0,302	0,360	0,579	0,296	0,442	0,692	0,286	0,602	0,788	0,382	0,159	0,581	0,004	0,146	0,097	0,319	0,125
RSOC	0,599	0,365	0,302	0,000	0,056	0,133	0,038	0,034	0,222	0,534	0,780	0,386	0,583	0,169	0,764	0,294	0,180	0,380	0,008	0,405
VAL	1,041	0,624	0,360	0,056	0,000	0,281	0,013	0,129	0,414	0,709	0,994	0,568	0,675	0,167	0,984	0,342	0,183	0,473	0,068	0,513
MAL	0,673	0,324	0,579	0,133	0,281	0,000	0,201	0,135	0,125	0,914	1,163	0,341	0,834	0,391	1,157	0,556	0,407	0,686	0,126	0,727
RBET	0,747	0,466	0,296	0,038	0,013	0,201	0,000	0,087	0,303	0,561	0,827	0,467	0,597	0,145	0,811	0,285	0,158	0,384	0,048	0,413
RVALL	0,797	0,449	0,442	0,034	0,129	0,135	0,087	0,000	0,256	0,763	1,029	0,442	0,729	0,262	1,019	0,424	0,277	0,546	0,025	0,583
SEV	0,536	0,201	0,692	0,222	0,414	0,125	0,303	0,256	0,000	1,032	1,265	0,243	0,919	0,501	1,261	0,665	0,518	0,800	0,217	0,843
GET	1,623	1,213	0,286	0,534	0,709	0,914	0,561	0,763	1,032	0,000	0,362	1,055	0,174	0,442	0,335	0,281	0,431	0,186	0,558	0,162
LEV	1,770	1,421	0,602	0,780	0,994	1,163	0,827	1,029	1,265	0,362	0,000	1,268	0,120	0,735	0,032	0,591	0,725	0,516	0,806	0,498
ATBIL	0,150	0,084	0,788	0,386	0,568	0,341	0,467	0,442	0,243	1,055	1,268	0,000	0,993	0,634	1,261	0,768	0,648	0,875	0,385	0,907
ESP	1,309	1,053	0,382	0,583	0,675	0,834	0,597	0,729	0,919	0,174	0,120	0,993	0,000	0,501	0,094	0,379	0,492	0,308	0,601	0,291
VALL	1,004	0,676	0,159	0,169	0,167	0,391	0,145	0,262	0,501	0,442	0,735	0,634	0,501	0,000	0,717	0,151	0,013	0,254	0,183	0,284
GRA	1,784	1,422	0,581	0,764	0,984	1,157	0,811	1,019	1,261	0,335	0,032	1,261	0,094	0,717	0,000	0,570	0,708	0,493	0,790	0,475
OSA	1,178	0,838	0,004	0,294	0,342	0,556	0,285	0,424	0,665	0,281	0,591	0,768	0,379	0,151	0,570	0,000	0,139	0,098	0,310	0,125
CVIG	1,025	0,693	0,146	0,180	0,183	0,407	0,158	0,277	0,518	0,431	0,725	0,648	0,492	0,013	0,708	0,139	0,000	0,242	0,194	0,271
MALL	1,346	0,977	0,097	0,380	0,473	0,686	0,384	0,546	0,800	0,186	0,516	0,875	0,308	0,254	0,493	0,098	0,242	0,000	0,400	0,027
DEP	0,606	0,364	0,319	0,008	0,068	0,126	0,048	0,025	0,217	0,558	0,806	0,385	0,601	0,183	0,790	0,310	0,194	0,400	0,000	0,425
ZAR	1,404	1,023	0,125	0,405	0,513	0,727	0,413	0,583	0,843	0,162	0,498	0,907	0,291	0,284	0,475	0,125	0,271	0,027	0,425	0,000

Team Clustering Cohen's *d* effect size matrix

	BAR	RM	ATM	RSOC	VAL	MAL	RBET	RVALL	SEV	GET	LEV	ATBIL	ESP	VALL	GRA	OSA	CVIG	MALL	DEP	ZAR
BAR	0,000	0,005	1,470	0,986	0,924	0,342	1,212	0,617	0,338	1,550	1,789	0,590	2,297	1,132	2,466	0,716	1,302	1,783	0,915	1,675
RM	0,005	0,000	1,204	0,797	0,711	0,263	0,966	0,489	0,264	1,181	1,512	0,490	1,822	0,955	2,079	0,641	1,013	1,449	0,766	1,295
ATM	1,470	1,204	0,000	0,429	0,611	1,071	0,292	0,781	1,040	0,170	0,384	0,677	0,531	0,170	0,930	0,303	0,298	0,221	0,380	0,033
RSOC	0,986	0,797	0,429	0,000	0,154	0,620	0,150	0,344	0,598	0,307	0,791	0,273	1,001	0,228	1,353	0,030	0,163	0,662	0,022	0,439
VAL	0,924	0,711	0,611	0,154	0,000	0,513	0,321	0,215	0,490	0,511	0,981	0,148	1,250	0,382	1,584	0,145	0,344	0,867	0,165	0,649
MAL	0,342	0,263	1,071	0,620	0,513	0,000	0,806	0,269	0,008	1,044	1,408	0,288	1,759	0,803	2,024	0,486	0,855	1,341	0,594	1,172
RBET	1,212	0,966	0,292	0,150	0,321	0,806	0,000	0,510	0,777	0,151	0,671	0,423	0,871	0,096	1,244	0,084	0,006	0,529	0,117	0,289
RVALL	0,617	0,489	0,781	0,344	0,215	0,269	0,510	0,000	0,254	0,705	1,129	0,044	1,404	0,548	1,713	0,290	0,540	1,030	0,342	0,834
SEV	0,338	0,264	1,040	0,598	0,490	0,008	0,777	0,254	0,000	1,004	1,374	0,275	1,705	0,780	1,977	0,474	0,822	1,302	0,575	1,130
GET	1,550	1,181	0,170	0,307	0,511	1,044	0,151	0,705	1,004	0,000	0,579	0,589	0,785	0,030	1,183	0,195	0,152	0,421	0,259	0,153
LEV	1,789	1,512	0,384	0,791	0,981	1,408	0,671	1,129	1,374	0,579	0,000	1,012	0,090	0,523	0,512	0,602	0,688	0,183	0,726	0,447
ATBIL	0,590	0,490	0,677	0,273	0,148	0,288	0,423	0,044	0,275	0,589	1,012	0,000	1,236	0,471	1,555	0,242	0,444	0,904	0,278	0,708
ESP	2,297	1,822	0,531	1,001	1,250	1,759	0,871	1,404	1,705	0,785	0,090	1,236	0,000	0,675	0,480	0,727	0,903	0,306	0,907	0,626
VALL	1,132	0,955	0,170	0,228	0,382	0,803	0,096	0,548	0,780	0,030	0,523	0,471	0,675	0,000	1,042	0,153	0,094	0,379	0,195	0,153
GRA	2,466	2,079	0,930	1,353	1,584	2,024	1,244	1,713	1,977	1,183	0,512	1,555	0,480	1,042	0,000	1,047	1,279	0,735	1,256	1,040
OSA	0,716	0,641	0,303	0,030	0,145	0,486	0,084	0,290	0,474	0,195	0,602	0,242	0,727	0,153	1,047	0,000	0,090	0,480	0,011	0,295
CVIG	1,302	1,013	0,298	0,163	0,344	0,855	0,006	0,540	0,822	0,152	0,688	0,444	0,903	0,094	1,279	0,090	0,000	0,544	0,127	0,296
MALL	1,783	1,449	0,221	0,662	0,867	1,341	0,529	1,030	1,302	0,421	0,183	0,904	0,306	0,379	0,735	0,480	0,544	0,000	0,596	0,277
DEP	0,915	0,766	0,380	0,022	0,165	0,594	0,117	0,342	0,575	0,259	0,726	0,278	0,907	0,195	1,256	0,011	0,127	0,596	0,000	0,381
ZAR	1,675	1,295	0,033	0,439	0,649	1,172	0,289	0,834	1,130	0,153	0,447	0,708	0,626	0,153	1,040	0,295	0,296	0,277	0,381	0,000

Team Intensity Cohen's *d* effect size matrix

	BAR	RM	ATM	RSOC	VAL	MAL	RBET	RVALL	SEV	GET	LEV	ATBIL	ESP	VALL	GRA	OSA	CVIG	MALL	DEP	ZAR
BAR	0,000	1,597	2,767	2,560	3,360	2,263	2,673	1,698	2,462	3,819	4,400	1,921	4,005	2,627	4,714	4,586	3,248	3,200	2,133	5,046
RM	1,597	0,000	0,749	0,667	0,929	0,103	0,790	0,275	0,532	1,381	1,953	0,077	1,606	0,654	2,104	1,848	1,050	1,256	0,332	2,268
ATM	2,767	0,749	0,000	0,061	0,119	1,217	0,087	1,266	0,237	0,682	1,375	1,022	0,963	0,103	1,545	1,222	0,322	0,623	0,434	1,734
RSOC	2,560	0,667	0,061	0,000	0,182	1,052	0,141	1,129	0,166	0,709	1,365	0,900	0,975	0,037	1,522	1,214	0,369	0,654	0,357	1,695
VAL	3,360	0,929	0,119	0,182	0,000	1,728	0,012	1,639	0,388	0,681	1,494	1,342	1,010	0,236	1,717	1,358	0,250	0,595	0,601	1,972
MAL	2,263	0,103	1,217	1,052	1,728	0,000	1,209	0,285	0,885	2,377	3,151	0,024	2,646	1,068	3,533	3,355	1,731	1,842	0,576	3,968
RBET	2,673	0,790	0,087	0,141	0,012	1,209	0,000	1,268	0,308	0,535	1,188	1,042	0,802	0,183	1,334	1,021	0,209	0,508	0,492	1,497
RVALL	1,698	0,275	1,266	1,129	1,639	0,285	1,268	0,000	0,980	2,193	2,875	0,254	2,442	1,138	3,144	2,911	1,691	1,830	0,708	3,436
SEV	2,462	0,532	0,237	0,166	0,388	0,885	0,308	0,980	0,000	0,928	1,596	0,745	1,195	0,134	1,769	1,465	0,563	0,833	0,203	1,960
GET	3,819	1,381	0,682	0,709	0,681	2,377	0,535	2,193	0,928	0,000	0,815	1,903	0,343	0,786	0,988	0,585	0,362	0,059	1,106	1,190
LEV	4,400	1,953	1,375	1,365	1,494	3,151	1,188	2,875	1,596	0,815	0,000	2,593	0,460	1,467	0,123	0,321	1,107	0,608	1,737	0,272
ATBIL	1,921	0,077	1,022	0,900	1,342	0,024	1,042	0,254	0,745	1,903	2,593	0,000	2,161	0,899	2,842	2,588	1,428	1,602	0,487	3,115
ESP	4,005	1,606	0,963	0,975	1,010	2,646	0,802	2,442	1,195	0,343	0,460	2,161	0,000	1,061	0,607	0,192	0,669	0,221	1,357	0,781
VALL	2,627	0,654	0,103	0,037	0,236	1,068	0,183	1,138	0,134	0,786	1,467	0,899	1,061	0,000	1,637	1,324	0,425	0,713	0,333	1,826
GRA	4,714	2,104	1,545	1,522	1,717	3,533	1,334	3,144	1,769	0,988	0,123	2,842	0,607	1,637	0,000	0,480	1,278	0,732	1,902	0,152
OSA	4,586	1,848	1,222	1,214	1,358	3,355	1,021	2,911	1,465	0,585	0,321	2,588	0,192	1,324	0,480	0,000	0,922	0,393	1,618	0,673
CVIG	3,248	1,050	0,322	0,369	0,250	1,731	0,209	1,691	0,563	0,362	1,107	1,428	0,669	0,425	1,278	0,922	0,000	0,352	0,752	1,472
MALL	3,200	1,256	0,623	0,654	0,595	1,842	0,508	1,830	0,833	0,059	0,608	1,602	0,221	0,713	0,732	0,393	0,352	0,000	0,995	0,875
DEP	2,133	0,332	0,434	0,357	0,601	0,576	0,492	0,708	0,203	1,106	1,737	0,487	1,357	0,333	1,902	1,618	0,752	0,995	0,000	2,083
ZAR	5,046	2,268	1,734	1,695	1,972	3,968	1,497	3,436	1,960	1,190	0,272	3,115	0,781	1,826	0,152	0,673	1,472	0,875	2,083	0,000